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Scale efficiency in Danish agriculture: an input distance–function approach

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Abstract

This paper presents the results of an analysis that predicts the scale efficiency of individual farms and analyses the differences in scale efficiency over time and between farms. Representative farm account data for 1985–2006 are used, and the study applies stochastic frontier analysis using an input distance–function approach. The results show that pig farms have improved their input scale efficiency significantly over time, as have dairy farms during the last few years after a period of constant scale efficiency. Crop farms have the lowest scale efficiency, and there is a considerable potential for improving productivity in the cash crop sector by increasing the size of the farms. It is shown that a change in scale efficiency and technological change are the major components of aggregate productivity changes for all farm types.

Keywords: stochastic frontier, scale efficiency, farm types, representative panel data, components of productivity change

JEL classification: C33, D24, Q12

1. Introduction

Productivity changes influence competitiveness and therefore the agricultural sector's economic performance. Historical data show that productivity growth in the agricultural sector varies considerably, both over time and between regions/countries. Lissitsa and Rungsuriyawiboon estimated that the total factor productivity of agriculture in the European Union (EU) had a growth rate of around 1.29 per cent per year during the 10-year period 1992–2002 with significant variability from one sub-period to the other and with considerable differences between countries.[1] Denmark ranks the highest with a total factor productivity increase of 2.61 per cent per year and Ireland ranks the

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1 Weighted average for the 15 pre-2004 member countries.

lowest with an increase of 0.49 per cent per year (Lissitsa and Rungsuriyawiboon, 2006).[2]

Other analyses confirm that Danish agriculture has had considerable productivity increases. Hansen has estimated that total factor productivity increased by 1.8 per cent per year from 1973 to 1980 and by 3.2 per cent per year from 1981 to 1993 (Hansen, 1990, 1995) with some differences between cash crop, dairy and pig farms. These changes were primarily attributable to technological changes (Hansen, 1995). Further analysis based on data from the period 1973–1995 shows that technological change was highest on cash crop farms (4.0 per cent per year) and lowest on dairy farms (1.0 per cent per year), with pig farms in between (2.2 per cent per year). The results also show that technological changes increased significantly over time during this period (Rasmussen, 2000).

Changes in agricultural productivity over time may be due to a number of individual factors. Technical changes are often considered as being the most important factor. However, the changes in the scale of production, changes in technical efficiency and changes in input and output composition may also contribute. The interesting question is which of these factors is the key component of productivity changes and how policy regulation may affect productivity and individual components of productivity changes.

Limited access to land and capital restricts farm growth and thereby related productivity changes as does policy regulation in the form of quantitative restrictions on the acquisition of farm land and other resources. In Denmark, ownership and the use of agricultural land is regulated by the Agriculture Act, which limits the amount of land a farmer is allowed to hold, while it also regulates ownership structure, the amalgamation of farms and restricts the number of livestock allowed per hectare of farm land.

The MacSharry reform in 1992 meant a considerable change in EU price policy. Crop price support was reduced considerably and a hectare premium for cultivating the affected crops and on fallow land was introduced as compensation. The change in the Danish environmental regulation in 1998 (Action Plan for the Aquatic Environment (Folketinget, 1998)) included a restriction on the nitrogen application to crops and from 1999 a tightening of the constraint on the number of animals per hectare. In the late part of the 1990s, pig production was also influenced by another type of regulation, namely the banning of anti-microbial growth promoters in 1995 and 1998 (Lawson *et al*., 2007).

While these rules and regulations fulfil certain political objectives, they also limit the farmers' ability to adjust the farm size according to economic and technological conditions. To the extent that the scale of operation is essential for productivity, rules and regulations that prevent farmers from reaching the efficient scale of operation will influence the productivity changes.

Rasmussen (2000) found that during the period 1973–1993 there was a considerable economic incentive to increase farm scale because the elasticity

2 Newman and Matthews (2007) report other measures of productivity change in Irish agriculture.

of size was larger than 1. However, there were considerable differences between farm types. Cash crop farms had the highest elasticity of size and therefore the highest incentive to increase the farm size. Dairy farms also had an incentive to increase the scale of operation, whereas pig farms had the lowest elasticity of size, suggesting that they faced the fewest restrictions on the ability to adjust to the optimal scale. The results indicate that scale efficiency varies from one farm type to another.

The primary objective of this paper is to study scale efficiency in Danish agriculture by comparing the differences in scale efficiency between different farm types and especially to elucidate the evolution of scale efficiency over time. The hypothesis is that there are differences in scale efficiency between farm types (as suggested by Rasmussen (2000)) and that these differences are related to regulatory measures. Cash crop farms have the highest incentive to increase the scale of operation because of restrictions on land acquisition. Dairy farms also have incentives to increase the scale of operation being restricted by the milk quota system. Pig farms probably have the lowest incentive to increase the scale of operation because this industry has been the least regulated. In this context it would be interesting to identify whether there is any connection between the changes in regulations and the development in scale efficiency. The paper seeks further to elucidate whether there is any relationship between scale efficiency, technical efficiency and key farm characteristics and how important the changes in scale efficiency are compared with other components of productivity change.

The methods used in the earlier analysis of productivity changes in Danish agriculture (Hansen, 1990, 1995) did not enable the decomposition of productivity change into its individual components. Hansen used a Fisher index to estimate indices of aggregate input and aggregate output. Rasmussen based his analysis on a cost–function approach. In the present paper, I use a distance–function approach, which facilities the decomposition of productivity changes and a specific analysis of changes in scale efficiency.

The distance–function approach to study the changes in agricultural productivity as done in this paper is not new. The essential tool is the stochastic frontier approach proposed by Aigner *et al*. (1977) and the distance–function, originally introduced by Shephard (1970). Over the years, this approach has been used by a number of authors to study agricultural productivity. Morrison-Paul *et al*. (2000) were the first to use this approach to formally analyse the consequences of regulatory changes in the components of productivity change. They estimated a four-output, seven-input stochastic output distance–function to analyse the impact of regulatory reforms on efficiency and adjustment of production processes on farms in New Zealand in the 1980s. Newman and Matthews (2007) used an output distance function to measure and decompose the productivity growth of Irish agriculture between 1984 and 2000 for four principal farming systems. Irz and Thirtle (2004) analysed the productivity performance for agriculture in Botswana between 1979–1996, using a two-output, six-input stochastic translog (TL) input distance–function. Abdulai and Tietje (2007) used data from 149 dairy farms in Schleswig-Holstein to estimate and compare seven different versions of stochastic frontier production functions to examine technical efficiency in the period 1997–2005. Sipiläinen (2007) used unbalanced panel data to estimate an input distance–function for 72 farms specialising in milk production from 1989–2000 and found that on average they had increasing returns to scale of 1.527.

Although I cannot claim any methodological originality for this analysis, I do claim originality in terms of the extensive data set on which the analysis is based. The data covers a representative sample of around 1,900 farms each year between 1985 and 2006, and the analysis of the individual farm types is based on 200–600 farms per year. The data set is a detailed source of information and this is the first study that provides a micro-based analysis of the components of productivity change that are nationally representative of the agricultural sector.[3] The main results are that the majority of Danish full-time farms operate below their optimal technical scale and that especially cash crop farms have low-scale efficiency. Scale efficiency has improved over time for crop and pig farms, whereas for dairy farms scale efficiency has improved significantly after the milk quota exchange market was established in Denmark in 1998. Aggregate changes in productivity are primarily due to changes in scale efficiency.

The remainder of the article is structured as follows. In Section 2, I review how the input distance function can be used to estimate the elasticity of scale (EOS) and I derived how to calculate scale efficiency based on the input distance function. In Section 3, the data are described while the empirical results are presented in Section 4. Section 5 provides a discussion and outlines some implications of the results. Finally, a conclusion is reached in Section 6.

2. Methodology

The paper follows methods similar to those used by Irz and Thirtle (2004), Newman and Matthews (2007) and Sipiläinen (2007). Irz and Thirtle and Sipiläinen used input distance functions, while Newman and Matthews used output distance functions. I used the input approach because one of the main enterprises studied is dairy farming where the milk quota regulation calls for an input orientation.[4] The specification of error and efficiency terms follows Battese and Coelli (1992).[5]

The input distance–function was first introduced by Shephard (1970). It describes how much an input vector may be proportionally contracted with

3 Newman and Matthews (2007) have made similar productivity analysis for Ireland.

4 Newman and Matthews (2007) discuss the choice of input versus output orientation. There is no specific reason for choosing the input orientation, except that the milk quota system would call for the use of the input orientation. If there is constant returns to scale the choice does not matter. However, as the results show, this is not the case here. Thus, there is a basis for further studies which compare input and output approaches.

5 Other models could have been used. The model proposed by Kumbhakar (2002) that includes risk preferences and production risk is an interesting alternative.

the output vector held fixed. The input distance–function D is formally defined as:

$$D(\mathbf{x}, \mathbf{y}, t, \mathbf{r}) = \max\left\{\theta : \theta > 0, \frac{x}{\theta} \in L(\mathbf{y}, t, \mathbf{r})\right\} \tag{1}$$

where θ is a scalar, $L(\mathbf{y}, t, \mathbf{r})$ is the set of input vectors, $\mathbf{x} = (x_1, \ldots, x_N) \in \mathcal{R}_+^N$ which in year t can produce the output vector $\mathbf{y} = (y_1, \ldots, y_M) \in \mathcal{R}_+^M$ given the vector $\boldsymbol{r} \in R^B$ of exogenous factors (regulatory variables). Thus,

$$L(\mathbf{y}, t, \mathbf{r}) = \{\mathbf{x} \in \mathcal{R}_+^N : \mathbf{x} \text{ can produce } \mathbf{y} \text{ given } \mathbf{r} \text{ in year } t\} \tag{2}$$

The input distance–function D is non-decreasing, linearly homogenous and concave in x, and non-increasing and quasi-concave in y (Färe and Primont, 1995). If $\mathbf{x} \in L(\mathbf{y}, t, \mathbf{r})$, then $D(\mathbf{x}, \mathbf{y}, t, \boldsymbol{r}) \geq 1$. If $\mathbf{x}$ belongs to the frontier of the input set (the isoquant of $\mathbf{y}$), then $D(\mathbf{x}, \mathbf{y}, t, \mathbf{r}) = 1$.

Following Lovell *et al.* (1994), I exploited the property of linear homogeneity of an input distance–function in inputs, i.e.

$$D(\lambda\mathbf{x}, \mathbf{y}, t, \mathbf{r}) = \lambda D(\mathbf{x}, \mathbf{y}, t, \mathbf{r}), \qquad \lambda > 0 \tag{3}$$

Setting $\lambda = 1/x_1$, where x_1 denotes the (arbitrarily chosen) first element of the input vector $\mathbf{x}$, equation (3) is expressed in logarithmic form as:

$$\ln D(\mathbf{x}, \mathbf{y}, t, \mathbf{r}) = \ln x_1 + \ln D\left(\frac{\mathbf{x}}{x_1}, \mathbf{y}, t, \mathbf{r}\right) \tag{4}$$

To empirically implement the distance function, a functional form must be specified. The obvious choice is the TL, which is also used in a distance–function context by Lovell *et al.* (1994), Coelli and Perelman (1996), Grosskopf *et al.* (1997), Morrison-Paul *et al.* (2000) and Balcombe *et al.* (2007). The TL is a flexible functional form and it has the advantage that it allows the EOS to vary for different farm sizes (Coelli *et al.* 1998).

The TL input distance–function with M outputs, N inputs, B regulatory variables and a time horizon of T is given by:

$$\begin{aligned}\ln D^t(\mathbf{x}, \mathbf{y}) = {} & \beta_0 + \sum_{n=1}^{N}\beta_n \ln x_n + \frac{1}{2}\sum_{n=1}^{N}\sum_{k=1}^{N}\beta_{nk}\ln x_n \ln x_k + \sum_{m=1}^{M}\alpha_m \ln y_m \\ & + \frac{1}{2}\sum_{m=1}^{M}\sum_{l=1}^{M}\alpha_{ml}\ln y_m \ln y_l + \sum_{m=1}^{M}\sum_{n=1}^{N}\gamma_{mn}\ln y_m \ln x_n + \sum_{n=1}^{N}\delta_{txn} t \ln x_n \\ & + \sum_{m=1}^{M}\delta_{tym} t \ln y_m + \sum_{s=2}^{T}\tau_s C_s + \sum_{r=1}^{B}\sum_{n=1}^{N}\theta_{rn} R_r \ln x_n + \sum_{r=1}^{B}\sum_{m=1}^{M}\kappa_{rm} R_r \ln y_m\end{aligned} \tag{5}$$

where D^t $(\mathbf{x}, \mathbf{y})$ is a measure of the radial distance from $(\mathbf{x}, \mathbf{y})$ to the production function in year t, t is a time index $(t = 1, \ldots, T)$, C_s $(s = 2, \ldots T)$ are time dummy variables with the value 1 if $s = t$ and zero otherwise and R_r

$(r = 1, \ldots, B)$ are regulatory dummy variables. All Greek letters are parameters of the TL function. As the input distance–function is linear homogeneous in inputs, the parameters in equation (5) must fulfil the following regularity restrictions: $\sum_n \beta_n = 1$; $\sum_k \beta_{nk} = 0$; $\sum_n \gamma_{mn} = 0$ $(m = 1, \ldots, M)$; $\sum_n \delta_{txn} = 0$; $\sum_n \theta_{rn} = 0$ $(r = 1, \ldots, B)$. I further imposed the symmetry conditions of the distance function by setting $\alpha_{ml} = \alpha_{lm}$ $(m, l = 1, \ldots, M)$ and $\beta_{nk} = \beta_{kn}$ $(n, k = 1, \ldots, N)$.

The condition for linear homogeneity is imposed by normalising the input vector by one of the inputs (see equations (3) and (4)). Choosing land (x_3) as the normalising input and including an index i for farms and t for time, I arrived at the following empirical model:[6]

$$
\begin{aligned}
-\ln(x_{3it}) = {} & \beta_0 + \delta d_{1it} + \sum_{n\neq 3}^{N} \beta_n \ln x^*_{nit} + \frac{1}{2}\sum_{n\neq 3}^{N}\sum_{k\neq 3}^{N} \beta_{nk} \ln x^*_{nit} \ln x^*_{kit} \\
& + \sum_{m=1}^{M} \alpha_m \ln y_{mit} + \frac{1}{2}\sum_{m=1}^{M}\sum_{l=1}^{M} \alpha_{ml} \ln y_{mit} \ln y_{lit} + \sum_{m=1}^{M}\sum_{n\neq 3}^{N} \gamma_{mn} \ln y_{mit} \ln x^*_{nit} \\
& + \sum_{n\neq 3}^{N} \delta_{txn} t \ln x^*_{n} + \sum_{m=1}^{M} \delta_{tym} t \ln y_{mit} + \sum_{s=2}^{T} \tau_s C_s + \sum_{r=1}^{B}\sum_{n\neq 3}^{N} \theta_{rn} R_r \ln x^*_{nit} \\
& + \sum_{r=1}^{B}\sum_{m=1}^{M} \kappa_{rm} R_r \ln y_{mit} + \sum_{k=1}^{2} \rho_k \mathrm{REG}_k + v_{it} - u_{it}
\end{aligned} \tag{6}
$$

where $x^*_{nit} = x_{\mathrm{nit}}/x_{3it}$ $(\forall n, i, t)$, v_{it} represent a random statistical noise and u_{it} is a technical inefficiency measure equal to $\ln D_i^t(\mathbf{x}_i, \mathbf{y}_i) \geq 0$ where $D_i^t(\mathbf{x}_i, \mathbf{y}_i) \geq 1$ is the value of the input distance–function of the i'th farm using the input vector $\mathbf{x}_i$ and producing the output vector $\mathbf{y}_i$ in year t. Notice that compared with equation (5), two new variables have been included in equation (6): The first one, d_{1it}, is a dummy variable that prepares the model for use when some of the input or output observations have zero values (Battese, 1997). The second one is REG_k, a dummy variable that controls for regional differences.[7]

Specification of the error term v_{it} follows the standard assumptions (Kumbhakar and Lovell, 2000), namely v_{it} is an independently and identically distributed (iid) random error term $N(0, \sigma_v^2)$. The inefficiency terms u_{it} are assumed to follow the specification:

$$u_{it} = u_i \exp(-\eta(t - T)) \tag{7}$$

6 The term $n \neq 3$ under the summation signs in equation (6) indicates that the summation from 1 to N excludes $n = 3$.

7 As shown in Rasmussen (2008), many of the farms in the data set had only one or two observations. The data set was therefore not rich enough to support the estimation of a real panel data model.

where u_i are farm specific inefficiency terms assumed to be *iid* as truncations at zero of the $N(\mu_i, \sigma_u^2)$ distribution, η is a parameter to be estimated and T is the last time period. This type of specification was first introduced by Battese and Coelli (1992) and was later applied by Newman and Matthews (2007). To explore the possibility of unobserved heterogeneity between farms and influence of policy regulation, the following four alternative specifications of the parameter μ_i (the expected value of the Normal distribution) were tested:

$$\begin{aligned}
&\text{Model 1}: \quad \mu_i = 0 \\
&\text{Model 2}: \quad \mu_i = \sum_{j=1}^{J-1} \varphi_j S_j \\
&\text{Model 3}: \quad \mu_i = \sum_{j=1}^{J-1} \varphi_j S_j + \sum_{k=1}^{K-1} \omega_k A_k \\
&\text{Model 4}: \quad \mu_i = \sum_{j=1}^{J-1} \varphi_j S_j + \sum_{k=1}^{K-1} \omega_k A_k + \sum_{r=1}^{B} \psi_r R_r
\end{aligned}$$

where S_j refers to size class dummy variables, A_k refers to age class dummy variables and R_r refers to regulatory dummy variables.

According to Battese and Coelli (1992), the minimum-mean-squared-error predictor of the technical efficiency (TE_{it}) of the i'th farm in time period t is:

$$\mathrm{TE}_{it} = E[\exp(-u_{it})|v_{it} - u_{it}] \tag{8}$$

The elasticity of the input distance–function with respect to inputs and outputs has useful interpretations. According to Färe and Primont (1995), the elasticity of D with respect to an output y_m, that is,

$$\begin{aligned}
\varepsilon^t_{D,\,y_m} &= \frac{\partial \ln D^t}{\partial \ln y_m} \\
&= \alpha_m + \sum_{l=1}^{M} \alpha_{ml} \ln y_l + \sum_{n=1}^{N} \gamma_{mn} \ln x_n + \delta_{tym} t + \sum_{r=1}^{B} \kappa_{rm} R_r
\end{aligned} \tag{9}$$

is equal to the negative of the elasticity of cost with respect to the output in question[8] for cost-minimising levels of input. Thus $\varepsilon^t_{D,\,y_m}$ reflects the relative importance of output y_m to the firm.

A corresponding measure and interpretation is available on the input side. For cost-minimising levels of input, the elasticity of D with respect to any

8 Chambers (1988) calls this term *cost flexibility* and its reciprocal *elasticity of size*.

input x_n equals its cost share s_n^t, i.e.

$$\varepsilon_{D,\,x_n}^t = \frac{\partial \ln D^t}{\partial \ln x_n}$$
$$= \beta_n + \sum_{k=1}^{N} \beta_{nk} \ln x_k + \sum_{m=1}^{M} \gamma_{mn} \ln y_m + \delta_{txn} t + \sum_{r=1}^{B} \theta_{rn} R_r = s_n^t \qquad (10)$$

The elasticity $\varepsilon_{D,\,x_n}^t$ therefore captures the relative importance of input x_n in the production process.

On the basis of equation (9), it is possible to estimate a local measure of *EOS* [9] as:

$$\varepsilon^t(\mathbf{x}^t, \mathbf{y}^t) = -\left[\sum_{m=1}^{M} \frac{\partial \ln D^t(\mathbf{x}^t, \mathbf{y}^t)}{\partial \ln y_m^t}\right]^{-1} \qquad (11)$$

This term can also be used to estimate the impact of policy regulation. The derivative of $\epsilon^t(x^t, y^t)^{-1}$ with respect to R_r is $-(\sum_{m=1}^{M} \kappa_{rm})$, which means that if $\sum_{m=1}^{M} \kappa_{rm}$ is positive (negative), then the EOS increases (decreases) as a result of implementing the regulation R_r. Graphically, this can be interpreted as a 'twist' of the production frontier, where the individual parameters (κ_{rm}, $m = 1, \ldots, M$) measure the relative contribution of each product.

Balk (2001) demonstrates that when there are variable returns to scale, total factor productivity defined in terms of the input distance function encompasses four independent factors of change, namely technical change (TC), technical efficiency change (TEC), scale efficiency change (SEC) and an input mix effect (IME). According to Balk (2001: 174), these terms can be estimated from the input distance–function as follows:

$$\mathrm{TC}^{s,t} = \left[\frac{D^t(\mathbf{x}^t, \mathbf{y}^t)}{D^s(\mathbf{x}^t, \mathbf{y}^t)} \times \frac{D^t(\mathbf{x}^s, \mathbf{y}^s)}{D^s(\mathbf{x}^s, \mathbf{y}^s)}\right]^{0.5} \qquad (12)$$

$$\mathrm{TEC}^{s,t} = \frac{D^s(\mathbf{x}^s, \mathbf{y}^s)}{D^t(\mathbf{x}^t, \mathbf{y}^t)} \qquad (13)$$

$$\mathrm{SEC}^{s,t} = \left[\frac{\mathrm{ISE}^t(\mathbf{x}^t, \mathbf{y}^t)}{\mathrm{ISE}^t(\mathbf{x}^t, \mathbf{y}^s)} \times \frac{\mathrm{ISE}^s(\mathbf{x}^s, \mathbf{y}^t)}{\mathrm{ISE}^s(\mathbf{x}^s, \mathbf{y}^s)}\right]^{0.5} \qquad (14)$$

$$\mathrm{IME}^{s,t} = \left[\frac{\mathrm{ISE}^s(\mathbf{x}^t, \mathbf{y}^t)}{\mathrm{ISE}^s(\mathbf{x}^s, \mathbf{y}^t)} \times \frac{\mathrm{ISE}^t(\mathbf{x}^t, \mathbf{y}^s)}{\mathrm{ISE}^t(\mathbf{x}^s, \mathbf{y}^s)}\right]^{0.5} \qquad (15)$$

where the changes are measured from time period s to time period t and the

9 This measure was proposed by Färe *et al.* (1986).

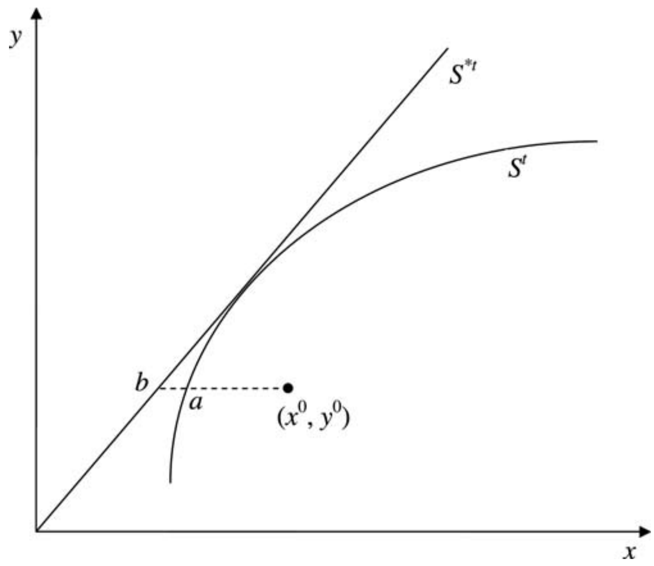

Fig. 1 Input-oriented scale efficiency.

input-oriented measures of scale efficiency (ISE) are calculated as:

$$\mathrm{ISE}^t(\mathbf{x}^t, \mathbf{y}^t) = \frac{D^t(\mathbf{x}^t, \mathbf{y}^t)}{D^{*t}(\mathbf{x}^t, \mathbf{y}^t)} \tag{16}$$

where – as before – $D^t(\mathbf{x}^t, \mathbf{y}^t)$ is measured relative to the technology set $S^t \subset \mathcal{R}_+^N \times \mathcal{R}_+^M$ of all feasible input–output combinations.

The new term $D^{*t}(\mathbf{x}^t, \mathbf{y}^t)$ is the value of the distance function measured relative to the *cone technology*, where the cone technology S^{*t} is defined relative to the actual technology (S^t) as: $S^{*t} = \{(\lambda x, \lambda y), (x, y) \in S^t, \lambda > 0\}$. The relation between the actual technology and the derived cone technology is illustrated for the $R_+^1 \times R_+^1$ case in Figure 1. From any point (x^0, y^0), $D^t(x^t, y^t)$ measures the distance relative to S^t (i.e. to point *a*), whereas $D^{*t}(\mathbf{x}^t, \mathbf{y}^t)$ measures the distance relative to S^{*t} (i.e. to point *b*).

According to Balk (2001: 174), the input distance–function $D^{*t}(\mathbf{x}^t, \mathbf{y}^t)$ is estimated as

$$D^{*t}(\mathbf{x}^t, \mathbf{y}^t) = \max_\lambda D^t(\lambda\mathbf{x}^t, \lambda\mathbf{y}^t) \tag{17}$$

Following a procedure similar to the one used by Balk (2001: 167), I arrived at the following solution to equation (17):[10]

$$\ln D(\lambda^*\mathbf{x}, \lambda^*\mathbf{y}) = \ln D(\mathbf{x}, \mathbf{y}) + \frac{1-\varepsilon(\mathbf{x}, \mathbf{y})}{\alpha\varepsilon(\mathbf{x}, \mathbf{y})}\left\{1 - \frac{1}{\varepsilon(\mathbf{x}, \mathbf{y})} + \frac{1-\varepsilon(\mathbf{x}, \mathbf{y})}{2\varepsilon(\mathbf{x}, \mathbf{y})}\right\} \tag{18}$$

10 The index *t* is left out here.

where λ^* is value of λ that maximises the right-hand side in equation (17), $\epsilon(\mathbf{x}, \mathbf{y})$ is the input-based EOS estimated as shown in equation (11) and α is the sum $\sum_{m=1}^{M}\sum_{l=1}^{M}\alpha_{ml}$ of coefficients in equation (5). Inserting equation (18) in equation (17) and solving for ISE using equation (16), I got the following equation describing the ISE:

$$\ln \mathrm{ISE}(\mathbf{x}, \mathbf{y}) = -\frac{1-\varepsilon(\mathbf{x},\ \mathbf{y})}{\alpha\varepsilon(\mathbf{x},\ \mathbf{y})}\left\{1-\frac{1}{\varepsilon(\mathbf{x},\ \mathbf{y})}+\frac{1-\varepsilon(\mathbf{x},\ \mathbf{y})}{2\varepsilon(\mathbf{x},\ \mathbf{y})}\right\} \tag{19}$$

3. Data and estimation

The data used are farm account data from the database of individual farm accounts collected by the Institute of Food and Resource Economics (FOI), University of Copenhagen. The farms included in the database are selected annually using stratified random sampling from the total Danish farm population to obtain representativity concerning farm size, geographical location and economic size (FOI, 2006). The data used in the present analysis cover the 22-year period (1985–2006) and comprises 41,926 observations. The number of observations per year is around 1,900 accounts, and each observation has a weight describing the number of farms it represents.[11] Around 70–80 per cent of the farms remain in the sample the following year. Hence, farms are, on average, represented in the sample for 3–5 subsequent years making the data set an unbalanced, rotating panel data set including 1,779 cash crop farms, 3,053 dairy farms and 2,319 pig farms. The data set is described in detail in Rasmussen (2008).

The data used in the present paper include only *full-time farms*, i.e. farms with a standard labour requirement of 1,665 h or more and comprises three independent sub-sets of the specialised farm types[12], *cash crop*, *dairy* and *pig farms*.

For each of the three sub-sets, the individual outputs were aggregated into two or three *main outputs*. For *crop farms*, two outputs are distinguished: (i) cash crop products (Y2)[13] and (ii) other products (Y9), which includes all cattle products, pigs and other animal products. For *dairy farms*, three outputs are distinguished: (i) cash crop products (Y2), (ii) cattle products (beef and milk) (Y3) and (iii) other products (Y7), which includes pigs and other animal products (except cattle products). For *pig farms*, three outputs

11 In the following, all averages within years are calculated as weighted averages.

12 The classification of farm systems is according to the definition of types of farming used in the EU agricultural statistics (FADN) (FOI, 2007). Crop farms comprise farms with more than two-thirds of the standard gross margin (SGM) from cash crops. Dairy farms comprise farms with more than two-thirds of the SGM from dairy cows, or at least one-third of the SGM from dairy cows and no other enterprise with more than one-third of the SGM. Pig farms comprise farms with more than two-thirds of the SGM from pigs, or at least one-third of the SGM from pigs and no other enterprise with more than one-third of the SGM.

13 The variable names used correspond to the variable names used in the paper describing the data set.

are distinguished: (i) cash crop products (Y2), (ii) pigs (Y4) and (iii) other products (Y8), which includes cattle products and other animal products (except pig products). The main product, *cash crops*, includes all the individual crops such as grain, grass seed, rape etc. as well as EU subsidies (area and single payment), subsidies for environmentally friendly agriculture (MVJ) and income from contractor operations. *Cattle products* include milk, beef and EU subsidies for suckling cows and male animals. *Pig products* include piglets and slaughter pigs.

Aggregation of outputs into the above-mentioned product categories was performed by dividing the total revenue of all the outputs in question with Törnqvist price indices for the output elements in question. The general form of the chain version[14] of a Törnqvist price index is calculated as:[15]

$$P^{t+1} = \left[\prod_{i=1}^{n} \left\{ \frac{p_i^{t+1}}{p_i^t} \right\}^{1/2\left(s_i^{t+1}+s_i^t\right)} \right] P^t \tag{20}$$

where P^t is the price index of the output aggregate in question (for instance, cash crop products) in year t, p_i^t is the price of output i in year t and s_i^t is the revenue share of output i in year t.

Inputs were aggregated into *six categories of aggregate inputs*: fertilisers (X1), feedstuff (X2), land (X3), labour (X4), machinery (X5) and other capital (X6). 'Land' (X3) is the hectares of land registered in the accounts multiplied by a quality index (see Rasmussen, 2008). 'Labour' (X4) is the number of working hours of the farmer, his family members and the paid labour registered in the accounts. The quantities of the remaining four inputs (fertilisers, feedstuff, machinery and other capital) were calculated by dividing the total cost of each of the four input types by the Törnqvist price index for the input elements involved. The procedure is the same as described above for the aggregation of output. 'Fertilisers' includes fertilisers, seed, pesticides, lime and other crop cost. 'Feedstuff' includes concentrates, roughage (bought) and veterinary services and medicine. 'Machinery' includes interest, depreciation, maintenance, insurance, contractors and fuel. 'Other capital' includes interest on stocks, interest, depreciation, maintenance and insurance on buildings, cost of insemination and control and energy. Individual interest measures are estimated for each asset type because asset-specific tax rules and asset-specific price changes were taken into account when calculating the asset-specific, tax-adjusted, real rate of interest. The input prices (p_i^t) used are prices from the yearly Agricultural Price Statistics from FOI. Prices in a given year are the same for all farms. The cost shares are determined in a similar way as the revenue shares mentioned above. A summary of the data is given in Table 1.

14 The advantage of using the chain principle for constructing indices is shown in Diewert (1978). See also Coelli *et al.* (2005).

15 For a detailed discussion of Törnqvist indices, see Diewert (1981).

Table 1. Descriptive statistics.[a] Units per farm (1985–2006)

	Unit[b]	Mean		Std. dev.	Min.	Max.
		Included	Deleted[c]			
Cash crop farms						
Obs. (*N*)	Number	5,206	(316)	5,206	5,206	5,206
Cash crop output (Y2)	EUR	146,094	(173,743)	153,845	4,170	3,722,390
Other output (Y9)	EUR	36,007	(5,160)	67,159	0	1,646,040
Fertilisers (X1)	EUR	30,809	(35,783)	29,113	974	1,228,130
Feedstuff (X2)	EUR	18,264	(2,814)	37,005	0	924,851
Land (X3)	Hectares	117	(154)	100	5	1,710
Labour (X4)	Hours	3,034	(3,066)	2,125	320	49,000
Machinery (X5)	EUR	44,853	(50,140)	43,340	541	933,395
Other capital (X6)	EUR	26,334	(24,693)	27,570	966	731,400
Dairy farms						
Obs. (*N*)	Number	12,828	(376)	12,828	12,828	12,828
Cash crop output (Y2)	EUR	25,481	(2,441)	31,771	7	902,848
Milk and beef output (Y3)	EUR	155,470	(113,013)	95,415	4,946	2,638,510
Other output (Y7)	EUR	8,125	(6,118)	28,346	0	716,866
Fertilisers (X1)	EUR	13,195	(6,421)	9,328	38	219,886
Feedstuff (X2)	EUR	47,712	(38,659)	36,837	495	1,125,240
Land (X3)	Hectares	63	(28)	40	0	681
Labour (X4)	Hours	3,708	(2,978)	1,509	600	25,700
Machinery X(5)	EUR	40,367	(23,257)	26,083	1,640	561,791
Other capital (X6)	EUR	35,463	(22,823)	21,446	2,307	467,859
Pig farms						
Obs. (*N*)	Number	8,925	(218)	8,925	8,925	8,925
Cash crop output (Y2)	EUR	49,885	(5,362)	47,649	7	763,420
Pig output (Y4)	EUR	271,407	(376,743)	239,431	13,165	3,565,440
Other output (Y8)	EUR	3,552	(6,636)	17,822	0	489,137
Fertilisers (X1)	EUR	15,408	(1,670)	12,034	19	248,160
Feedstuff (X2)	EUR	127,169	(194,514)	111,704	3,331	1,832,330
Land (X3)	Hectares	73	(10)	52	0	644
Labour (X4)	Hours	4,060	(4,295)	2,549	700	33,200
Machinery (X5)	EUR	49,056	(42,977)	40,545	1,860	651,726
Other capital (X6)	EUR	56,603	(71,790)	46,430	4,106	838,996

Source: FOI (2007).
[a]Weighted averages within years using number of farms represented by each observation in the sample. Simple averages over years.
[b]DKK converted into EUR using an exchange rate of DKK 745 per EUR 100.
[c]Observations not included in the analysis. See text.

For cash crop farms, a large number of observations had zero value for the output variable Y9 (animal products) and the input variable X2 (feedstuff). To avoid missing observations,[16] I used a dummy variable (d_1) such that the two variables were not included in the model when they (both) had zero values.[17] The same method was used for dairy farms when the output variable Y7 (other animal products than dairy and beef) was zero and for pig farms when the output variable Y8 (other animal products than pig products) was zero.[18] The method is described in Battese (1997). Two dummy variables were included in the model to account for differences in soil quality and climate between the various regions of Denmark. The two dummy variables separate 'The Islands' ($REG_1 = 1$) from 'Eastern Jutland' ($REG_2 = 1$) and 'Western Jutland' (benchmark).

Individual estimations were carried out for *cash crop farms*, *pig farms* and *dairy farms*. Estimation of the model was performed using the BC-model in LIMDEP version 9.0 (Greene, 2007). Before estimation, all the variables were normalised by their respective overall averages.

4. Results

4.1. Test of model specification

Farms were classified into three size classes ($J = 3$) according to standard gross margin and farmers into three age classes ($K = 3$). Farms were defined as large ($j = 3$) if they belonged to the upper quartile in the specific year, as small ($j = 1$) if they belonged to the lower quartile in the specific year, and as middle sized ($j = 2$) if they were in between. Farmers were classified as young ($k = 1$) if they were below the age of 45 years, as old ($k = 3$) if they were 55 years or older and as middle aged ($k = 2$) if they were in between. Concerning policy regulation, it was decided to test the impact of the MacSharry reform in 1992 and the environmental regulation introduced in 1998. Accordingly, R_1 is a dummy variable with the value 1 in 1999 and later years and R_2 is a dummy variable with the value 1 in 1993 and later years.

The specification of the inefficiency term was tested using the likelihood ratio test. The alternative models tested are Models 1, 2, 3 and 4 mentioned in Section 2. As shown in Table 2, both farm size and farmer age contribute significantly to the explanation of production inefficiency. However, the regulatory variables R_1 and R_2 did not contribute to the explanation of production inefficiency and the inefficiency Model 3 was therefore used in the following.

16 It is not possible to take the logarithm of a zero value.

17 The observation was deleted if just one of the two variables had a zero value. The observation was also deleted if any of the other inputs had a zero value. For cash crop farms, a total of 316 observations were deleted (out of a total of 5,522; see Table 1).

18 Both for dairy farms and for pig farms observations were deleted if any of the input variables were zero, or if crop production (Y2) was zero. For dairy farms, a total of 376 (out of 13,206 observations) were deleted. For pig farms, a total of 218 (out of 9,143 observations) were deleted (see Table 1).

Table 2. Likelihood Ratio tests[a] on specification of inefficiency term

Model	Crop farms				Dairy farms				Pig farms			
	1	2	3	4	1	2	3	4	1	2	3	4
Log likelihood	2,481	2,509	2,520	2,522	12,389	12,397	12,407	12,410	8,164	8,171	8,178	8,180
Likelihood ratio		56.9	22.6	4.3		17.4	19.3	5.8		13.8	12.8	4.5

[a]5 per cent critical for all tests equals 5.99.

A complete list of parameter estimates for each of the three farm types is shown in Tables A1, A2 and A3 in the Appendix.

All the parameter estimates have the appropriate sign ($\alpha_m < 0$) for all m outputs and $\beta_n > 0$ for all n inputs) and monotonicity conditions are therefore fulfilled at the sample mean. Monotonicity was also tested for the entire sample. Monotonicity is not violated if input elasticities are positive and output elasticities are negative. The number of violations are shown in Table 3 together with the input and output elasticities at the sample mean.

There are only very few violations for all inputs and the main outputs. The three estimated distance functions therefore seem quite robust in fulfilling the theoretical conditions of being non-decreasing and concave in **x** and non-increasing and quasi-concave in **y**.

The output elasticities reported in Table 3 measure the relative contribution to the EOS according to equation (11). On the basis of overall weighted averages of explanatory variables, the predicted EOS for crop, dairy and pig farms is 1.384 (0.011)[19], 1.260 (0.004) and 1.192 (0.005), respectively, which suggests that for the period as a whole, crop, dairy and pig farms are below their technical optimal scale, but that dairy and pig farms are closer to the technical optimal scale[20] than crop farms.

4.2. Estimated technical efficiency, input scale elasticity and EOS

The mean technical efficiency was calculated for each year using weighted averages of u_{it} in equation (8). The results are shown in Table 4. The table also includes the predicted EOS and the predicted input scale elasticity (ISE) based on weighted averages of explanatory variables within each year.

4.2.1. Technical efficiency

The average technical efficiency is considerably lower on crop farms (0.82) than on dairy (0.88) and pig farms (0.90). However, one should be careful when making comparisons, as the estimated technical efficiency scores on crop, dairy and pig farms do not refer to the same production frontier. Furthermore, it is likely that the predicted mean efficiency of pig farms is high because the sample of pig farms is more homogeneous than the other farm types.

The efficiency measures (TE) in Table 4 are at the same level as estimated by other authors. Key *et al.* (2008) found an average technical efficiency of 0.70 for a sample of around 500 American hog farms in 1992, 1998 and 2004, using a stochastic frontier approach. Hadley (2006) estimated a predicted average technical efficiency of 0.754, 0.897 and 0.887 for English and Welsh cereal, dairy and pig farms, respectively, for the period 1982–2002. He used random farm samples consisting of 702, 1431 and 199 farms, respectively, and applied stochastic frontier analysis. These figures correspond well with the findings in this paper, especially the fact that crop farms

19 The figures in parentheses are standard errors.

20 Technical optimal scale is defined as the scale, where EOS is 1.

Table 3. Elasticities of input–distance function at (weighted) sample means

	Outputs				Inputs					
	Crop	Dairy	Pigs	Other	Fertiliser	Feed	Land	Labour	Machine	Capital
Crop farms	−0.574			−0.149	0.159	0.078	0.211	0.306	0.154	0.092
Std.	0.004			0.004	0.008	0.004	0.024	0.008	0.007	0.006
Violations	0			164	30	142	18	3	196	5
Dairy farms	−0.112	−0.623		−0.059	0.053	0.219	0.123	0.312	0.129	0.164
Std.	0.001	0.003		0.001	0.003	0.003	0.010	0.004	0.004	0.004
Violations	315	8		1,027	257	7	39	8	42	1
Pig farms	−0.143		−0.666	−0.030	0.066	0.384	0.081	0.228	0.104	0.136
Std.	0.002		0.003	0.001	0.005	0.004	0.014	0.006	0.006	0.005
Violations	77		0	404	64	3	33	0	57	5

Table 4. Predicted technical efficiency (TE), elasticity of scale (EOS) and input scale efficiency (ISE). Based on weighted average over farms within years.

	Crop farms					Dairy farms					Pig farms				
Year	Obs	EOS	EOS Std	TE	ISE	Obs	EOS	EOS Std	TE	ISE	Obs	EOS	EOS Std	TE	ISE
1985	252	1.341	0.016	0.83	0.81	669	1.247	0.006	0.88	0.90	393	1.246	0.008	0.90	0.83
1986	271	1.381	0.015	0.84	0.78	670	1.254	0.006	0.88	0.90	398	1.244	0.007	0.90	0.83
1987	274	1.424	0.014	0.83	0.75	621	1.277	0.006	0.88	0.88	398	1.235	0.007	0.90	0.84
1988	240	1.372	0.012	0.80	0.79	604	1.262	0.005	0.87	0.89	406	1.221	0.006	0.89	0.85
1989	251	1.364	0.012	0.82	0.79	596	1.265	0.005	0.88	0.89	411	1.200	0.006	0.89	0.88
1990	258	1.339	0.013	0.81	0.81	612	1.301	0.006	0.88	0.87	372	1.216	0.006	0.90	0.86
1991	266	1.354	0.014	0.81	0.80	614	1.290	0.006	0.88	0.87	400	1.201	0.006	0.90	0.87
1992	253	1.367	0.016	0.81	0.79	584	1.278	0.006	0.87	0.88	416	1.197	0.007	0.90	0.88
1993	211	1.416	0.018	0.81	0.76	608	1.262	0.007	0.88	0.89	370	1.201	0.007	0.90	0.87
1994	207	1.430	0.016	0.83	0.75	599	1.282	0.007	0.88	0.88	405	1.203	0.007	0.90	0.87
1995	238	1.433	0.016	0.82	0.74	619	1.284	0.006	0.88	0.88	395	1.206	0.007	0.89	0.87
1996	220	1.430	0.017	0.81	0.75	645	1.279	0.006	0.88	0.88	416	1.208	0.007	0.90	0.87
1997	196	1.407	0.017	0.82	0.76	605	1.268	0.006	0.87	0.89	410	1.207	0.007	0.90	0.87
1998	170	1.424	0.019	0.83	0.75	494	1.250	0.007	0.88	0.90	333	1.189	0.007	0.90	0.89
1999	188	1.365	0.019	0.82	0.79	569	1.264	0.006	0.88	0.89	388	1.178	0.006	0.91	0.90
2000	213	1.360	0.018	0.82	0.80	612	1.269	0.006	0.88	0.89	429	1.172	0.006	0.90	0.90
2001	246	1.372	0.017	0.83	0.79	596	1.264	0.006	0.88	0.89	456	1.171	0.005	0.91	0.90
2002	245	1.380	0.017	0.83	0.78	586	1.250	0.006	0.88	0.90	447	1.170	0.006	0.90	0.90
2003	257	1.375	0.017	0.83	0.79	533	1.240	0.006	0.88	0.91	393	1.161	0.006	0.91	0.91
2004	249	1.397	0.018	0.84	0.77	503	1.233	0.006	0.88	0.91	440	1.152	0.006	0.90	0.92
2005	255	1.368	0.019	0.83	0.79	483	1.214	0.007	0.88	0.92	436	1.138	0.007	0.90	0.93
2006	246	1.362	0.021	0.82	0.80	406	1.190	0.007	0.88	0.93	413	1.128	0.007	0.90	0.94
Average	237	1.385		0.82	0.78	583	1.260		0.88	0.89	406	1.193		0.90	0.88

have considerably lower technical efficiency than dairy and pig farms. Brümmer et al. (2002) found an average technical efficiency in 1994 of 0.979, 0.953 and 0.904 for dairy farms in Germany (128), Poland (200) and The Netherlands (564),[21] respectively, based on an output distance function approach. Sipiläinen (2007) found an average technical efficiency of 0.913 for a sample of 72 specialised Finnish dairy farms over the period 1990–2000 based on the estimation of an input distance–function.

Table 4 shows a constant technical efficiency through time for all three farm types. However, the estimated value of the parameter η (see equation (7)), is negative and significant for all three farm types (t-test, 5 per cent test level. See Table A1, A2 and A3 in the Appendix).[22] This indicates a *decline in the within-farm technical efficiency* through time. To explain the constant technical efficiency for the sample as a whole, new farms entering the sample must on average have a higher technical efficiency than the farms remaining in the sample.

The estimated parameters (φ_j and ω_k) of the inefficiency term (see Table A1, A2 and A3 in the Appendix) show that technical efficiency decreases with farmer age and farm size. Old farmers have a significantly lower technical efficiency than middle aged and young farmers except for dairy farms, where middle aged farmers have a significantly higher efficiency than young and old farmers. Large farms have a significantly lower efficiency than small farms for all farms types, while for crop farms, large farms also have a significantly lower efficiency than middle sized farms.

4.2.2. Elasticity of scale

The results in Table 4 show that the average EOS is greater than 1, indicating increasing returns to scale. On average, only 1.7 per cent of the cash crop farms, 3.4 per cent of the dairy farms and 3.8 per cent of the pig farms have an EOS less than 1.05. For dairy and pig farms, the EOS has declined over time, suggesting that the farms – on average – have moved from a smaller towards a larger and more efficient scale of production.[23]

The impact of policy regulation on the EOS depends on the value of $\sum_{m=1}^{M} \kappa_{rm}$. For R_1, the value for crop, dairy and pig farms is -0.0198 (0.0157), -0.0051 (0.0060) and -0.0045 (0.0072), respectively.[24] The negative values suggest that the environmental regulation introduced in 1998 has reduced the EOS,[25] but the impact is statistically insignificant. However, all the coefficients for cash crop products (κ_{12}) are negative and significant,

21 The figures in parentheses are the number of farms in the sample.

22 The 5 per cent test level is used throughout.

23 The standard deviations of the estimated elasticities af scale (EOS Std) were estimated using a second-order Taylor approximation, according to which

$$\mathrm{Var}(1/x) \cong x^{-4}\,\mathrm{Var}(x).$$

24 The figures in parentheses are standard errors.

25 This corresponds to a twist of the production function so that it becomes more flat (the slope decreases).

indicating that the marginal productivity in cash crop production has decreased for all three farm types. For R_2, the value of $\sum_{m=1}^{M} \kappa_{2m}$ for crop, dairy, and pig farms is 0.0486 (0.0137), −0.0126 (0.0061), and 0.0118 (0.0074), respectively. The positive number for crop farms is significant, which means that R_2 (MacSharry reform in 1992) induced an increasing EOS (the marginal productivity increased significantly for both cash crops ($\kappa_{22} > 0$) and other products ($\kappa_{29} > 0$)). This is also the case with pig farms, but here the impact is insignificant. For dairy farms, the impact of the MacSharry reform was a reduction in the EOS, but the impact is hardly significant.

4.2.3. Input scale efficiency

The ISEs in Table 4 essentially tell the same story as the EOS. The increasing scale efficiency for pig farms has taken place at a slow and steady rate, suggesting that the scale of pig farms has gradually increased, not only towards a larger scale of production measured in absolute terms, but also towards a more efficient scale. In the case of dairy farms, the mean scale efficiency was relatively constant at a level around 0.88 until the year 2000, after which the scale efficiency increased – especially in the last 2 years – to a level of 0.94 in 2006. Thus, even though the average number of dairy cows per full-time farm increased from 35 in 1985 to 62 in 2000 (FOI, year), dairy farms did not move any closer to the technical optimal scale during this period. After the turn of the century, the average number of dairy cows per full-time farm increased from 62 in 2000 to 97 in 2006 (FOI, 2000, 2006), which apparently was sufficient to move dairy farms towards a more efficient scale of production. Crop farms have had considerably lower scale efficiency than dairy and pig farms at the beginning of the period and the gap has even widened during the last years.

The results are illustrated in Figure 2.

4.2.4. Components of productivity change

Changes in the ISE contribute to productivity change. Indices of year-to-year productivity change calculated as TFP = TEC*TC*SEC*IME are shown in Table 5. TFP varies considerably over time due to the fact that year-to-year changes in growing conditions (weather) are captured by the technical change (TC) component through the dummy year variable (C_s). Other year specific changes are also captured by the corresponding dummy year variable and therefore materialise in the technical change component. The year-to-year variations due to changing weather conditions smooth out over time and the *average* of the technical change component is therefore considered an unbiased estimate of the real average technical change over the period in question.

If I consider the whole period, total factor productivity has increased by 3.3 per cent per year on crop farms, 2.4 per cent per year on dairy farms and by 2.1 per cent on pig farms. Changes in scale efficiency and technical change provide the major contribution, while the aggregate of changes in technical efficiency and input mix provide only a minor contribution.

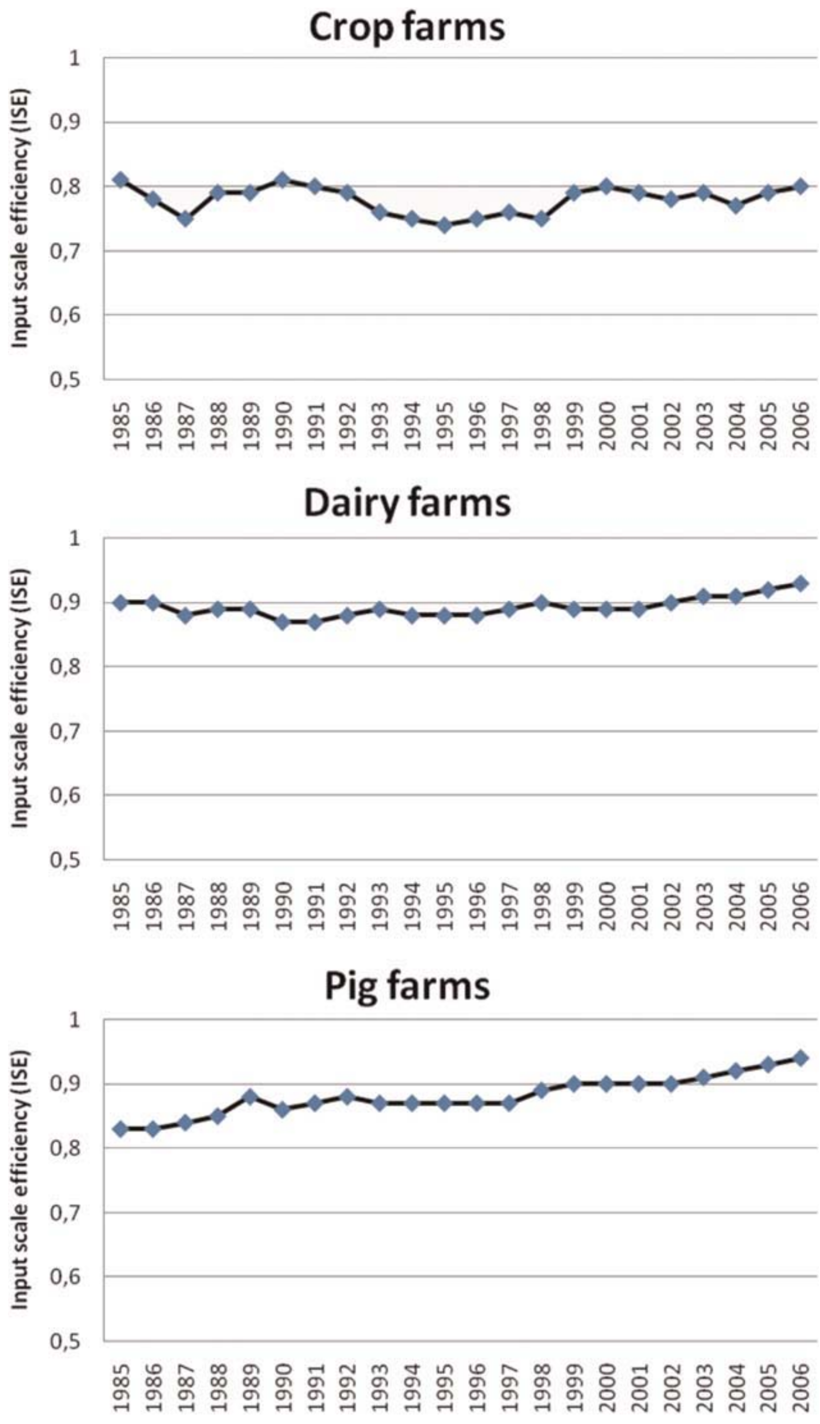

Fig. 2 Predicted input scale efficiency (ISE) for crop, dairy and pig farms 1986–2006.

Table 5. Indices of year-to-year changes in technical efficiency (TEC), technical change (TC), input scale efficiency (SEC), input mix effect (IME) and total factor productivity (TFP)

	Crop Farms					Dairy farms					Pig farms				
Year	TEC	TC	SEC	IME	TFP	TEC	TC	SEC	IME	TFP	TEC	TC	SEC	IME	TFP
1985															
1986	0.985	1.016	0.976	0.999	0.975	1.008	0.957	1.005	0.998	0.967	0.989	1.008	1.011	0.997	1.004
1987	1.012	0.972	0.972	1.002	0.957	0.992	1.003	0.999	0.992	0.985	1.017	1.031	1.020	0.996	1.065
1988	0.972	1.109	1.067	0.998	1.148	0.989	1.086	1.016	1.003	1.095	1.002	1.090	1.021	1.000	1.116
1989	1.014	1.055	1.022	0.999	1.092	1.014	1.011	1.007	0.998	1.030	1.000	1.029	1.027	1.002	1.059
1990	1.027	1.006	1.018	1.018	1.071	1.008	0.955	0.990	0.992	0.945	1.002	0.925	0.998	0.989	0.914
1991	1.022	0.935	1.002	0.996	0.953	1.035	1.017	1.023	0.994	1.070	1.018	1.051	1.027	0.995	1.093
1992	0.992	0.967	0.994	1.006	0.960	0.963	0.976	1.023	0.994	0.956	1.005	0.957	1.010	0.998	0.969
1993	1.003	1.135	1.056	1.001	1.203	0.995	1.088	1.006	0.998	1.088	0.983	1.101	1.024	0.995	1.103
1994	0.988	0.988	1.001	0.999	0.976	0.995	0.977	0.999	0.995	0.966	1.008	1.008	1.005	0.997	1.019
1995	0.999	1.028	1.009	1.003	1.039	0.994	1.014	1.010	0.996	1.014	0.986	1.004	1.001	1.001	0.991
1996	0.984	1.030	1.014	1.003	1.031	1.007	1.021	1.016	0.996	1.041	0.997	0.997	1.005	0.997	0.996
1997	1.015	1.025	1.033	1.003	1.079	0.994	1.039	1.018	0.997	1.049	0.996	0.985	1.006	0.999	0.985
1998	1.036	0.987	0.997	1.001	1.021	1.006	1.007	1.027	0.993	1.033	1.006	1.012	1.027	0.998	1.043
1999	0.985	0.998	1.029	1.004	1.014	1.001	0.990	1.004	0.988	0.983	1.014	1.031	1.011	0.997	1.055
2000	1.021	1.019	1.005	1.013	1.058	0.993	1.009	1.007	0.997	1.006	0.996	0.980	1.011	1.000	0.986
2001	0.994	0.982	1.008	0.994	0.978	0.997	0.998	1.011	1.000	1.006	1.012	0.954	1.003	1.001	0.970
2002	0.993	1.001	1.008	0.998	0.999	1.011	1.017	1.023	0.995	1.047	0.974	1.017	1.007	0.998	0.996
2003	1.002	1.036	1.019	0.998	1.056	0.982	1.024	1.019	0.995	1.019	1.000	1.013	1.014	0.999	1.027
2004	1.022	0.972	0.982	1.010	0.986	0.995	1.030	1.016	0.996	1.036	0.989	0.991	1.013	0.999	0.992
2005	0.996	1.026	1.044	0.997	1.065	1.011	1.066	1.025	0.995	1.098	1.018	1.014	1.022	0.994	1.049
2006	0.979	1.065	1.021	0.999	1.063	1.006	1.058	1.016	1.005	1.088	1.005	1.026	1.011	1.001	1.043
Average	1.002	1.016	1.013	1.002	1.033	1.000	1.016	1.012	0.996	1.024	1.001	1.010	1.013	0.998	1.021

5. Discussion

The estimation of the individual input distance-function models for crop, dairy and pig farms performed well. The fact that these individual estimations provided comparable results adds to the confidence that the data and the model are well chosen and provide reliable results.

The use of representative panel data provides the opportunity to *register changes* over time for *representative* farms. When interpreting the results, one should be aware that these changes include both within-farm changes and between-farm changes. The changes in efficiency scores through time, therefore, refer to the sector as such, and not the individual farms.

The ISE has increased over time for dairy and pig farms. However, crop farms are still at a relatively low-scale efficiency level of 0.78 in 2006, despite the fact that the average size of the full-time cash crop farms has increased from 85 hectares in 1985 to 159 hectares in 2006 (SJI, 1987; FOI, 2007), almost doubling the farm size when measured in hectares of land. The results are in accordance with the results found by Rasmussen (2000), and they support the hypothesis that restrictions concerning acquisition of farm land severely restrict the ability of crop farms to adjust the farm.

The analysis does *not* show any relationship between scale efficiency and farmer age. On the other hand, technical efficiency decreases with farmer age and farm size. This result suggests that small farms, on average, are more careful producers and put more effort into the efficient use of inputs than large farms. This may be their way of compensating for not (being able to) producing at the optimal scale. Apparently, young farmers are more careful producers than old farmers, maybe because their education is more up to date, or because their economic situation is more vulnerable than old farmers.

Technical efficiency has stayed almost constant over time for all three farm types, and the reforms in 1992 and 1998 had no direct impact on technical efficiency. In his analysis of Finnish farms, Sipiläinen (2007) found that technical efficiency declined over time. The decline was a total decline of 5 per cent over an 11-year period. Hadley (2006) found a declining efficiency in English/Welsh agriculture from 1982 to 2002. The decline was about 10 per cent on both dairy and pig farms and about 20 per cent on crop farms. Hadley also suggested that the average farm is falling behind the efficient frontier, which means that the gap between the farms that are pushing the frontier outwards and the farms that are trying to catch up is widening. As mentioned earlier, the results presented in this paper are representative of the Danish full-time farming sector as a whole and they do not necessarily correspond to within-farm changes in efficiency estimated in other studies.

Earlier analysis (Hansen, 1995) suggests that the major source of productivity change in Danish agriculture is the technological change. The results in the present paper suggest that the changes in ISE is also an important source of aggregate productivity change during the period considered.

6. Conclusion

More than 95 per cent of Danish full-time farms have increasing returns to scale, which means that they operate below their optimal technical scale (scale efficiency less than 1). Only very few farms operate above their technical optimal scale. The ISE is considerably lower in the cash crop sector than in the dairy and pig sectors. The reason for the low ISE in the crop sector is probably due to restrictions on the acquisition of farm land and other resources preventing farmers from acquiring enough land to take full advantage of the technological development. However, there may be other reasons, for instance budget constraints.

Pig farms have improved their ISE significantly over the time period considered, as have dairy farms during the last couple of years after a period of constant scale efficiency. The gradual improvement in scale efficiency in the pig sector suggests that the changes in policy regulation during the period considered have had no distinctive influence on the adjustment towards a more optimal scale of production. However, the improvement of the scale efficiency of dairy farms after 2000 could very well be due to the introduction of the milk quota exchange market in 1999 that improved the flexibility regarding structural development. Stricter rules regarding livestock density on farm land introduced in 1998 apparently did not influence the adjustment of farm scale on dairy and pig farms, but the environmental regulation in 1998 had a negative impact on the marginal productivity in cash crop production. The MacSharry reform in 1992 had a positive impact on the marginal productivity on crop farms, but the impact on dairy and pigs farms was insignificant.

Technical efficiency has stayed constant through time on all three farm types and the policy reforms analysed have had no impact on technical efficiency. However, technical efficiency decreases with farmer age and farm size for all farm types.

As an average over the 22-year period, productivity change has been highest on cash crop farms (3.3 per cent per year), lowest on pig farms (2.1 per cent per year) with dairy farms in between (2.4 per cent per year). The major components of productivity changes are the changes in ISE and in the technical change. The changes in the technical efficiency and input mix have only contributed marginally to aggregate the changes in productivity. This result suggests that regulatory measures, which prevent individual farms from adjusting their scale of operation to the technical optimal scale, may have important implications for productivity growth in the agricultural sector.

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Appendix: parameter estimates

Table A1. Estimated parameters. Cash crop farms

Variable	Coefficient	Standard error	t-Ratio
β_0	−0.1004	0.0144	−6.9790
δ	0.2210	0.0065	34.1020
α_2	−0.7542	0.0112	−67.5610
α_9	−0.1441	0.0102	−14.1820
β_1	0.2499	0.0195	12.7960
β_2	0.0676	0.0097	6.9900
β_4	0.1636	0.0220	7.4200
β_5	0.1883	0.0170	11.0510
β_6	0.0557	0.0156	3.5660
α_{22}	−0.1710	0.0054	−31.4000
α_{99}	−0.0288	0.0031	−9.3400
α_{29}	0.0230	0.0034	6.7860
β_{11}	0.0737	0.0164	4.4910
β_{22}	0.0186	0.0031	5.9050
β_{44}	0.1350	0.0254	5.3120
β_{55}	0.1853	0.0129	14.3740
β_{66}	0.0265	0.0130	2.0400
β_{12}	0.0075	0.0068	1.0970
β_{14}	0.0493	0.0183	2.6910
β_{15}	−0.0900	0.0152	−5.9110
β_{16}	0.0099	0.0132	0.7470
β_{24}	−0.0275	0.0097	−2.8370
β_{25}	0.0111	0.0079	1.4020
β_{26}	0.0038	0.0069	0.5530
β_{45}	−0.0590	0.0146	−4.0490
β_{46}	−0.0298	0.0148	−2.0160
β_{56}	−0.0142	0.0114	−1.2420
γ_{21}	0.0122	0.0087	1.3900
γ_{91}	−0.0002	0.0074	−0.0280
γ_{22}	−0.0114	0.0036	−3.1640
γ_{92}	−0.0022	0.0029	−0.7680
γ_{24}	−0.0401	0.0092	−4.3390
γ_{94}	0.0334	0.0097	3.4400
γ_{25}	0.0428	0.0089	4.7970
γ_{95}	−0.0123	0.0081	−1.5220
γ_{26}	0.0038	0.0072	0.5350

(continued)

Table A1. (*continued*)

Variable	Coefficient	Standard error	*t*-Ratio
γ_{96}	−0.0105	0.0068	−1.5370
δ_{tx1}	−0.0104	0.0027	−3.8720
δ_{tx2}	0.0029	0.0013	2.2120
δ_{tx4}	0.0062	0.0030	2.0890
δ_{tx5}	0.0038	0.0027	1.4370
δ_{tx6}	0.0017	0.0021	0.8320
δ_{ty2}	0.0117	0.0014	8.6210
δ_{ty9}	−0.0044	0.0013	−3.4910
ρ_1	0.0803	0.0081	9.9330
ρ_2	0.0136	0.0093	1.4670
θ_{R11}	0.0806	0.0249	3.2420
θ_{R12}	−0.0266	0.0114	−2.3370
θ_{R13}	0.0585	0.0287	
θ_{R14}	−0.0862	0.0272	−3.1690
θ_{R15}	−0.0553	0.0243	−2.2800
θ_{R16}	0.0290	0.0197	1.4670
κ_{R12}	−0.0520	0.0118	−4.4250
κ_{R19}	0.0322	0.0115	2.8050
θ_{R21}	0.0030	0.0238	0.1250
θ_{R22}	−0.0097	0.0112	−0.8700
θ_{R23}	−0.0728	0.0259	
θ_{R24}	0.1353	0.0239	5.6530
θ_{R25}	−0.0611	0.0220	−2.7820
θ_{R26}	0.0053	0.0180	0.2950
κ_{R22}	0.0262	0.0107	2.4580
κ_{R29}	0.0224	0.0106	2.1140
τ_{86}	0.0112	0.0136	0.8220
τ_{87}	−0.0078	0.0126	−0.6160
τ_{88}	0.0971	0.0137	7.0870
τ_{89}	0.1546	0.0135	11.4780
τ_{90}	0.1723	0.0146	11.8260
τ_{91}	0.1123	0.0148	7.5990
τ_{92}	0.0813	0.0144	5.6410
τ_{93}	0.2164	0.0149	14.4890
τ_{94}	0.1944	0.0151	12.8950
τ_{95}	0.2221	0.0161	13.8200
τ_{96}	0.2521	0.0163	15.4310
τ_{97}	0.2783	0.0160	17.3840
τ_{98}	0.2769	0.0179	15.4610
τ_{99}	0.2599	0.0165	15.7950
τ_{00}	0.2793	0.0162	17.2640
τ_{01}	0.2550	0.0156	16.3740
τ_{02}	0.2574	0.0160	16.0930

(*continued*)

Table A1. (*continued*)

Variable	Coefficient	Standard error	t-Ratio
τ_{03}	0.2909	0.0159	18.2620
τ_{04}	0.2631	0.0168	15.6960
τ_{05}	0.2829	0.0151	18.7770
τ_{06}	0.3415	0.0162	21.0810
ω_1	−0.0515	0.0353	−1.4570
ω_3	0.0821	0.0272	3.0180
φ_1	−0.4776	0.1652	−2.8920
φ_3	0.3397	0.0587	5.7860
$\sigma = \sqrt{\sigma_v^2 + \sigma_u^2}$	0.2800	0.0009	306.0210
$\lambda = \sigma_u/\sigma_v$	2.5009	0.0136	183.9180
η	−0.0259	0.0016	−15.9760
L	2,520		

Table A2. Estimated parameters. Dairy farms

Variable	Coefficient	Standard error	t-Ratio
β_0	−0.1018	0.0084	−12.0750
δ	0.1760	0.0025	71.6130
α_2	−0.0950	0.0027	−35.0340
α_3	−0.7363	0.0060	−123.0790
α_7	−0.0783	0.0015	−51.9440
β_1	0.0522	0.0081	6.4430
β_2	0.2337	0.0083	28.2380
β_4	0.2341	0.0120	19.4700
β_5	0.1623	0.0122	13.3170
β_6	0.1913	0.0135	14.1780
α_{22}	−0.0248	0.0005	−45.4230
α_{33}	−0.2511	0.0034	−73.9410
α_{77}	−0.0150	0.0003	−50.2400
α_{23}	0.0459	0.0013	36.1450
α_{27}	−0.0004	0.0003	−1.1640
α_{37}	0.0067	0.0008	8.5790
β_{11}	0.0305	0.0062	4.9290
β_{22}	0.0405	0.0065	6.2580
β_{44}	0.0648	0.0103	6.3140
β_{55}	0.0376	0.0153	2.4570
β_{66}	0.0590	0.0102	5.8050
β_{12}	0.0333	0.0054	6.2060
β_{14}	−0.0780	0.0079	−9.8440
β_{15}	0.0029	0.0076	0.3780
β_{16}	0.0046	0.0084	0.5520

(*continued*)

Table A2. (*continued*)

Variable	Coefficient	Standard error	t-Ratio
β_{24}	0.0194	0.0078	2.4690
β_{25}	0.0143	0.0078	1.8330
β_{26}	−0.0198	0.0076	−2.6190
β_{45}	−0.0513	0.0109	−4.7090
β_{46}	−0.0003	0.0116	−0.0270
β_{56}	−0.0201	0.0103	−1.9500
γ_{21}	−0.0100	0.0018	−5.6070
γ_{31}	−0.0318	0.0035	−9.0440
γ_{71}	0.0007	0.0011	0.6830
γ_{22}	−0.0147	0.0018	−8.1770
γ_{32}	0.0396	0.0035	11.3950
γ_{72}	−0.0049	0.0010	−4.6770
γ_{24}	0.0315	0.0024	13.0800
γ_{34}	−0.1206	0.0052	−23.2280
γ_{74}	0.0085	0.0015	5.5550
γ_{25}	−0.0108	0.0024	−4.4710
γ_{35}	0.0448	0.0047	9.4750
γ_{75}	−0.0023	0.0015	−1.5600
γ_{26}	0.0177	0.0025	7.1920
γ_{36}	0.0100	0.0052	1.9250
γ_{76}	−0.0014	0.0016	−0.8940
δ_{tx1}	−0.0027	0.0010	−2.7880
δ_{tx2}	−0.0028	0.0010	−2.8620
δ_{tx4}	0.0056	0.0014	3.9330
δ_{tx5}	0.0006	0.0014	0.4170
δ_{tx6}	0.0002	0.0016	0.1400
δ_{ty2}	−0.0008	0.0003	−2.6120
δ_{ty3}	0.0074	0.0007	10.6730
δ_{ty7}	0.0001	0.0002	0.7430
ρ_1	0.0490	0.0042	11.5700
ρ_2	−0.0049	0.0030	−1.6280
θ_{R11}	0.0252	0.0084	3.0010
θ_{R12}	0.0101	0.0076	1.3320
θ_{R13}	0.0585	0.0287	
θ_{R14}	−0.0431	0.0133	−3.2340
θ_{R15}	−0.0036	0.0119	−0.3080
θ_{R16}	0.0127	0.0135	0.9410
κ_{R12}	−0.0104	0.0032	−3.2290
κ_{R13}	0.0053	0.0054	0.9750
κ_{R17}	0.0000	0.0016	−0.0230
θ_{R21}	0.0275	0.0088	3.1200
θ_{R22}	0.0161	0.0082	1.9720
θ_{R23}	−0.0728	0.0259	

(*continued*)

Table A2. (*continued*)

Variable	Coefficient	Standard error	*t*-Ratio
θ_{R24}	0.0234	0.0123	1.9120
θ_{R25}	−0.0438	0.0116	−3.7780
θ_{R26}	−0.0422	0.0124	−3.3990
κ_{R22}	−0.0067	0.0027	−2.4660
κ_{R23}	−0.0061	0.0060	−1.0140
κ_{R27}	0.0002	0.0014	0.1100
τ_{86}	−0.0397	0.0052	−7.5930
τ_{87}	−0.0381	0.0052	−7.3670
τ_{88}	0.0436	0.0058	7.4590
τ_{89}	0.0596	0.0065	9.1950
τ_{90}	0.0191	0.0067	2.8390
τ_{91}	0.0380	0.0073	5.2050
τ_{92}	0.0161	0.0081	1.9960
τ_{93}	0.0805	0.0076	10.5460
τ_{94}	0.0573	0.0080	7.1690
τ_{95}	0.0695	0.0083	8.3800
τ_{96}	0.0919	0.0085	10.8370
τ_{97}	0.1292	0.0087	14.8210
τ_{98}	0.1368	0.0087	15.6650
τ_{99}	0.1249	0.0088	14.1910
τ_{00}	0.1327	0.0089	14.9660
τ_{01}	0.1284	0.0088	14.6500
τ_{02}	0.1454	0.0089	16.4320
τ_{03}	0.1651	0.0093	17.6710
τ_{04}	0.1929	0.0087	22.1270
τ_{05}	0.2523	0.0088	28.6630
τ_{06}	0.3078	0.0089	34.6860
ω_1	0.0321	0.0136	2.3690
ω_3	0.0595	0.0128	4.6520
φ_1	−0.0994	0.0409	−2.4300
φ_3	0.0767	0.0405	1.8950
$\sigma = \sqrt{\sigma_v^2 + \sigma_u^2}$	0.1747	0.0002	1133.6260
$\lambda = \sigma_u/\sigma_v$	2.3734	0.0094	251.7260
η	−0.0124	0.0015	−8.0260
L	12,407		

Table A3. Estimated parameters. Pig farms

Variable	Coefficient	Standard error	t-Ratio
β_0	−0.1569	0.0123	−12.7240
δ	0.0958	0.0033	29.1470
α_2	−0.1379	0.0047	−29.5980
α_4	−0.7327	0.0082	−89.6330
α_8	−0.0476	0.0032	−14.9780
β_1	0.0527	0.0125	4.2120
β_2	0.4486	0.0108	41.5890
β_4	0.1665	0.0169	9.8460
β_5	0.1389	0.0150	9.2850
β_6	0.1149	0.0165	6.9410
α_{22}	−0.0359	0.0007	−48.2270
α_{44}	−0.1296	0.0052	−24.7550
α_{88}	−0.0104	0.0007	−14.2320
α_{24}	0.0327	0.0020	16.6680
α_{28}	0.0010	0.0008	1.2990
α_{48}	0.0024	0.0013	1.7910
β_{11}	0.0245	0.0063	3.9010
β_{22}	0.1924	0.0101	19.1400
β_{44}	0.1196	0.0167	7.1720
β_{55}	0.0590	0.0168	3.5120
β_{66}	−0.0091	0.0176	−0.5150
β_{12}	−0.0202	0.0082	−2.4590
β_{14}	0.0001	0.0124	0.0090
β_{15}	−0.0123	0.0097	−1.2580
β_{16}	0.0228	0.0131	1.7480
β_{24}	−0.0374	0.0108	−3.4670
β_{25}	−0.0484	0.0093	−5.1930
β_{26}	−0.0337	0.0114	−2.9630
β_{45}	−0.0795	0.0154	−5.1640
β_{46}	−0.0138	0.0158	−0.8720
β_{56}	0.0477	0.0130	3.6810
γ_{21}	0.0079	0.0027	2.8570
γ_{41}	−0.0232	0.0053	−4.3880
γ_{81}	−0.0025	0.0024	−1.0240
γ_{22}	0.0117	0.0028	4.1260
γ_{42}	−0.0209	0.0053	−3.9130
γ_{82}	−0.0007	0.0017	−0.4100
γ_{24}	0.0027	0.0041	0.6600
γ_{44}	−0.0260	0.0080	−3.2430
γ_{84}	0.0024	0.0031	0.7830
γ_{25}	−0.0099	0.0036	−2.7490
γ_{45}	0.0196	0.0070	2.8020
γ_{85}	−0.0009	0.0027	−0.3430

(*continued*)

Table A3. (*continued*)

Variable	Coefficient	Standard error	t-Ratio
γ_{26}	−0.0099	0.0043	−2.3100
γ_{46}	0.0415	0.0078	5.3040
γ_{86}	−0.0019	0.0029	−0.6660
δ_{tx1}	−0.0008	0.0015	−0.5470
δ_{tx2}	−0.0059	0.0012	−4.7870
δ_{tx4}	0.0038	0.0021	1.7730
δ_{tx5}	0.0019	0.0018	1.0540
δ_{tx6}	0.0037	0.0021	1.7360
δ_{ty2}	0.0002	0.0005	0.4390
δ_{ty4}	0.0022	0.0009	2.3060
δ_{ty8}	0.0002	0.0003	0.6600
ρ_1	0.0352	0.0047	7.5260
ρ_2	0.0127	0.0038	3.3510
θ_{R11}	0.0277	0.0127	2.1850
θ_{R12}	0.0014	0.0105	0.1290
θ_{R13}	0.0109	0.0151	
θ_{R14}	−0.0550	0.0180	−3.0620
θ_{R15}	−0.0151	0.0151	−0.9960
θ_{R16}	0.0301	0.0183	1.6480
κ_{R12}	−0.0267	0.0046	−5.8250
κ_{R14}	0.0229	0.0074	3.1140
κ_{R18}	−0.0007	0.0028	−0.2550
θ_{R21}	0.0048	0.0139	0.3500
θ_{R22}	0.0219	0.0103	2.1300
θ_{R23}	0.0475	0.0154	
θ_{R24}	0.0302	0.0161	1.8740
θ_{R25}	−0.0644	0.0140	−4.6030
θ_{R26}	−0.0401	0.0166	−2.4200
κ_{R22}	0.0022	0.0042	0.5310
κ_{R24}	0.0090	0.0079	1.1440
κ_{R28}	0.0006	0.0025	0.2310
τ_{86}	0.0083	0.0069	1.2050
τ_{87}	0.0386	0.0073	5.2900
τ_{88}	0.1281	0.0083	15.4310
τ_{89}	0.1577	0.0092	17.2200
τ_{90}	0.0810	0.0103	7.8290
τ_{91}	0.1345	0.0106	12.6520
τ_{92}	0.0912	0.0113	8.0550
τ_{93}	0.1872	0.0111	16.8880
τ_{94}	0.1982	0.0118	16.8300
τ_{95}	0.2022	0.0121	16.6440
τ_{96}	0.1969	0.0121	16.2750
τ_{97}	0.1816	0.0120	15.0770

(*continued*)

Table A3. (*continued*)

Variable	Coefficient	Standard error	t-Ratio
τ_{98}	0.1960	0.0123	15.8970
τ_{99}	0.2264	0.0120	18.9050
τ_{00}	0.2052	0.0123	16.6800
τ_{01}	0.1576	0.0123	12.8070
τ_{02}	0.1737	0.0125	13.9390
τ_{03}	0.1880	0.0123	15.3200
τ_{04}	0.1792	0.0122	14.7480
τ_{05}	0.1945	0.0122	15.9140
τ_{06}	0.2195	0.0120	18.3280
ω_1	−0.0118	0.0159	−0.7400
ω_3	0.0368	0.0144	2.5470
φ_1	−0.1205	0.0412	−2.9260
φ_3	0.0371	0.0348	1.0660
$\sigma = \sqrt{\sigma_v^2 + \sigma_u^2}$	0.1475	0.0001	1046.8130
$\lambda = \sigma_u/\sigma_v$	1.8280	0.0153	119.8200
η	−0.0231	0.0025	−9.2070
L	8,178		